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Detecting apple abscission during robotic harvesting with force and pressure sensing ⋆

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Abstract: Robotic apple harvesting is a complex operation requiring efficient coordination among multiple subsystems including fruit detection, gripping/grasping, picking, and storage. A robot that can accurately detect the moment a fruit is picked can adjust its behavior dynamically, moving directly from the picking task to the next task in the pipeline, such as fruit storage. Similarly, a robot that can determine whether it has failed to pick an attempted fruit can estimate the crop load remaining in the orchard, field, etc. after harvesting. In this paper, we present a simple approach that uses feedback from pressure and force sensors to predict the moment an apple has been separated from the tree. To evaluate our approach, we completed field experiments at a research orchard in Randwijk, Netherlands. Postprocessing the data, we manually annotated in videos the moment of apple abscission and compared the annotations with the algorithm's predictions. Over 35 samples, the algorithm's F1 score was 0.95, and the average time difference between the user's manual annotations and the predicted time of abscission was 0.59 +/- 0.42 sec.

Keywords: Robotic harvesting, apple abscission, suction gripper, force sensor, pressure sensor

1. INTRODUCTION

In robotic fruit harvesting, accurately detecting the moment a fruit is picked is important for improving harvesting efficiency. A robot capable of identifying successful fruit detachment can adapt its behavior dynamically, moving directly from the picking task to fruit storage, reducing unnecessary movements and maximizing operational speed. In contrast, detecting a failed pick attempt enables the robot to immediately retry the pick, or to move on and record the missed fruit's location in a map. Detailed information about fruit remaining in the orchard (e.g. fruit distribution maps) could then be used by growers to plan follow-up harvesting with human workers, increasing yields. To increase the likelihood of adoption, a method for pick detection should be cost-effective, robust, and generalizable across fruit varieties and orchard systems.

While there has been extensive work on vision for fruit detection and localization, detecting abscission in cluttered and occluded plant canopies using camera-based techniques would be very challenging. More recently, there has been an increase in the use of in-hand sensing (Dischinger et al. (2021)) such as tactile sensing (Mandil et al. (2023); Elfferich et al. (2022)) during robotic harvesting. Typically, tactile sensing has been used during the *grasping phase* (i.e. when the end-effector attempts to secure the fruit); a few examples include using tactile sensors to control the grip force applied to strawberries (Visentin et al. (2023); Rajendran et al. (2024)) and sense finger obstructions from branches during robotic apple harvesting (Zhou et al. (2023)). One way that tactile sensing has been used during the *pick phase* is to detect and react to slip (Zhou et al. (2022)) between the gripper and fruit. Some challenges with integrating tactile sensors are cost and long-term robustness in agricultural environments, as well as difficulties embedding tactile sensors with some gripper morphologies, such as those that use suction cups.

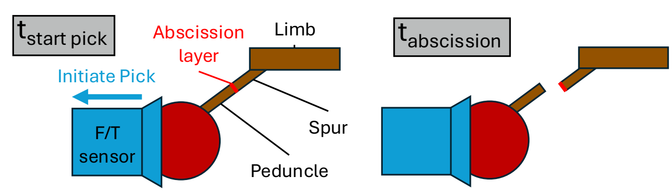

Fig. 1. Apple abscission during robotic harvesting. Our goal is detect the moment the fruit is picked from the tree, $t_{abscission}$.

In this paper, we present a pick detection technique for robotic apple harvesting that uses in-hand sensors to predict the moment that the fruit is separated from the tree (see Fig. 1). Our approach is most similar to slip

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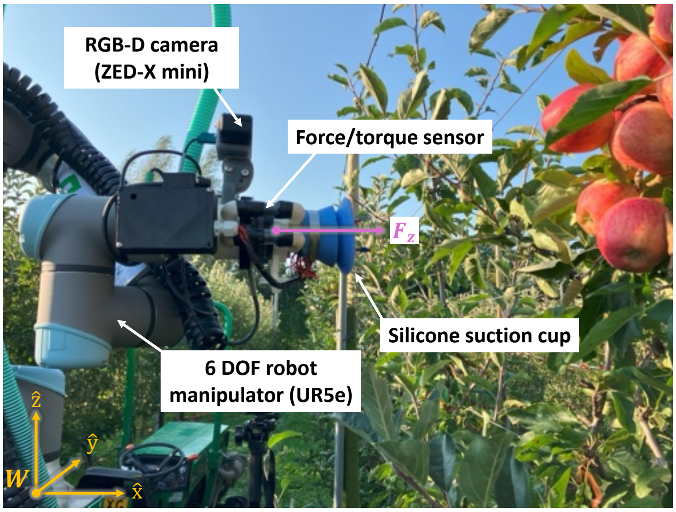

Fig. 2. Experimental setup. The apple harvesting gripper uses a custom soft suction cup. The integrated system includes an eye-in-hand camera configuration, pressure sensor, and a 6-axis force/torque sensor mounted between the gripper and the manipulator. The $z-axis$ of the force sensor passes through the central axis of the suction cup.

detection, but rather than try to detect transient slip as it occurs, we study a slightly different question – *at what time was the apple picked or missed*? The technique uses force sensing from a force-torque sensor mounted on the robot's wrist instead of tactile sensing from the gripper. To evaluate the technique, we conducted robotic harvesting experiments in realistic field conditions at a research orchard in the Netherlands. Our primary contribution is a computationally simple, intuitive heuristic that requires no data collection, learning, or model training.

2. METHODS

Our robotic apple harvesting system integrates a compliant suction cup, in-line pressure sensor, and a wrist force/torque sensor. During the picking phase, a simple heuristic algorithm uses realtime pressure and force measurements to detect the moment the apple is picked from the tree. To validate our approach, we compared the algorithm's classifications and event detection times with synchronized videos from real world apple picks.

2.1 Hardware description

The apple picking gripper, shown in Fig. 2, is a custom soft suction cup developed at Wageningen University and Research (van Damme (2024)). For picking experiments, the gripper was mounted on a 6 degree-of-freedom UR5e manipulator (Universal Robots, Odense, Denmark). The pneumatic system (i.e. vacuum pump, solenoid valves, and pressure sensors) are integrated with the UR5e's industrial controller. For measuring forces during harvesting, there is a 6-axis Robotiq (Québec, Canada) FT300 force/torque sensor mounted between the suction cup and the manipulator's tool flange. A ZED-X mini RGB-D sensor (StereoLabs, San Francisco, USA) mounted above the suction cup in an 'eye-in-hand' configuration is used for fruit detection and localization.

2.2 Pick detection algorithm

Picking an apple is a dynamic action. The intuition behind our approach is that fruit abscission is a mechanical 'disturbance' that should be detectable in the wrist force sensor. Figure 3 shows the gripper's synchronized x-y position (i.e. the gripper's coordinates in the $\hat{x} - \hat{y}$ plane; see Fig. 2 for the location of the fixed world frame W at the robot's base), wrist force, and suction cup pressure during each phase of an example apple pick, shaded in different colors. Suction during the fruit *grip* phase (green) registers a high force normal to the wrist force/torque sensor. As the robot starts to *pick* the fruit, shown shaded in pink, an additional load from the resistance of the tree is applied that is generally opposite in direction to the suction force/suction cup. The moment the fruit is severed at the abscission joint, the load from the limb is quickly removed, which appears as a small positive force impulse as vacuum pulls in the compliant suction cup. During the pick, there is a slight change in pressure as the suction cup is deformed (but for a successful pick, suction is maintained until the fruit is released). An unsuccessful pick where the fruit slips from the gripper can be seen from a premature sharp rise in pressure.

To detect abscission, our simple algorithm looks for large transients in the force signal. First, starting at the onset of the picking phase, at each time step we calculate the 2-norm of $F_x(t)$, $F_y(t)$, and $F_z(t)$ as measured by the force/torque sensor (the three torque components are not used):

$$||F(t)||_2 = \sqrt{F_x(t)^2 + F_y(t)^2 + F_z(t)^2} \tag{1}$$

Then, we calculate a numerical derivative of force using the central finite difference:

$$dF(t) = \frac{dF}{dt} = \frac{3F_j - 4F_{j-\Delta t} + F_{j-2\Delta t}}{2\Delta t} \tag{2}$$

where F is the value of the force at the current index j. We then smooth the derivative with a weighted moving average ($d\widetilde{F}(t)$) over a fixed-length buffer of recent derivative values. Let L denote the total number of samples collected during the picking phase so far, and let w be the moving average window size:

$$d\widetilde{F}(t) = \frac{1}{w}\left(\sum_{j=1}^{L-w+1} dF_j\right) \tag{3}$$

The remaining logic is straightforward – if there is a positive spike in the derivative and vacuum is maintained, the algorithm estimates that the apple has been *picked*. For this work, we set the threshold to $d\widetilde{F}(t) = 1$, which was experimentally determined through trial and error. If the pressure in the suction gripper rises back to ambient air pressure (i.e. the surrounding atmospheric pressure) without reaching this threshold, we assume that the fruit was *missed* – indicating that suction was lost before a successful pick could be finished.

2.3 Data collection

To evaluate our approach, we conducted robotic harvesting field experiments and postprocessed the data. Figure 2

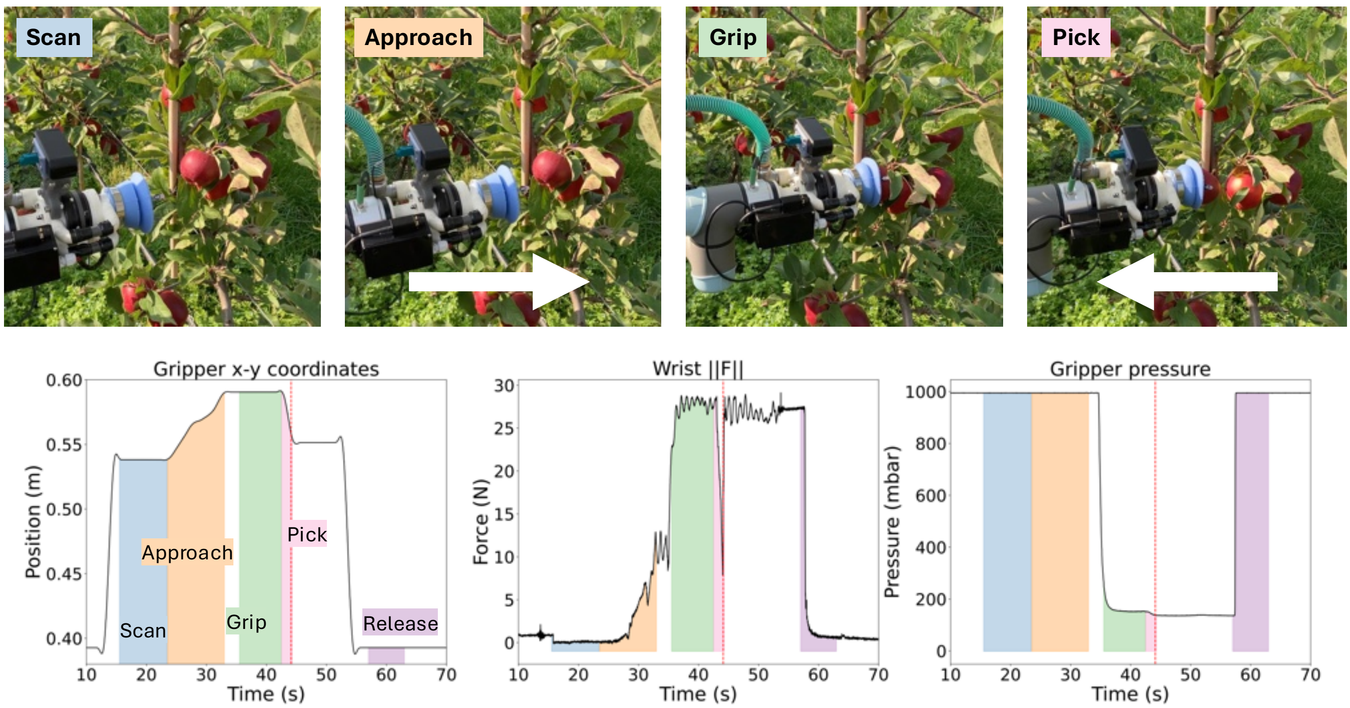

Fig. 3. Top row: Images of the different phases during apple harvesting. Bottom row: Sensor signals corresponding to the same phases of a successful apple pick, with color shading indicating each phase. The (*left*) plot shows the gripper's vertical position (z-axis) in meters as it moves over time, the (*center*) plot shows the normalized wrist force, and the (*right*) plot shows the gripper's pressure. The dashed red vertical line indicates the moment the fruit separates from the tree.

shows the experimental setup used for data collection. Experiments were completed in Randwijk, Netherlands in September 2024 with 'Gala' apples cultivated using a high density, 2-dimensional trellised training system. Our protocol was to pick a single apple in each iteration using the sequence of detect fruit, approach fruit, grip fruit, pick fruit.

We used RGB-D images from the ZED-X mini for fruit detection and localization. Fruit detection in the color image was completed with deep learning instance segmentation. For this step a YoloV8 (Jocher et al. (2023)) model was trained with manually annotated apple images. Transfer learning from the default pre-trained model on the COCO dataset was applied. To determine the center of an apple and to reduce the disturbing effects of partial fruit occlusion (by i.e. leaves, branches or incomplete segmentations) a minimum enclosing circle was fit on the mask of each segmented apple. The center of this circle was taken as the center of the apple. To calculate the distance of the apple with respect to the camera, the median of all available depth values of the corresponding depth image inside a circle drawn at the center of the enclosing circle with 0.1*radius of the enclosing circle was used (Fig. 4). Together with the 2D image coordinates of the center of the apple and the intrinsics of the camera, the 3D position of the fruit in the camera coordinate system was calculated. This position was then transformed into the robot base frame W and used as the target gripping point. Before the experiments, an eye-in-hand calibration was performed to determine the relative position and orientation of the camera with respect to the robot's end effector. Another

Fig. 4. Camera image with result of apple detection. Shown are the detected apple instances (green contour), enclosing circle (white circle), and region used for distance measurement (small red circle inside white circle)

time-synchronized camera on a static tripod recorded the scene.

We used Robot Operating System 2 (ROS2 Humble) (Macenski et al. (2022)) on Ubuntu 22.04 for control and communication. To perform each pick, we transmitted a twist command via ROS2 to the robot that included a linear pull along the negative z-axis of the robot's wrist and an angular twist about the same axis. The linear pull speed was set to 0.5m/s, and the twist was set to 3 rad/s. We recorded the robot's pose and the output of the force/torque sensor in the robot's wrist as ROS2 topics. The pose was sampled at a rate of 10 Hz using a transform

Fig. 5. User Interface for determining moment of abscission. The user was provided a video of the pick (*right*), as well as the z-position of the gripper (*left*), and was given a button to press when the pick occurred. The force signals were not provided to the subject.

listener in MoveIt. The Robotiq FT300 sensor broadcasts the force and torque data at a rate of 100 Hz.

We manually recorded grip success, pick success, and measured the size and damage, if any, for each pick attempt. We only postprocessed the data for those trials where the initial grip of the apple was successful (i.e. we did not evaluate the algorithm for attempts where there was a fruit localization error, there was a failed grip due to a branch obstruction, etc.).

2.4 Evaluation

Our performance evaluation included two metrics, classification accuracy, i.e. was the classification correct, and time accuracy, i.e. did the classification occur at the moment of abscission. To evaluate time accuracy, we created a PyQt [1] interface that displayed the evolution of the robot's pose with the synchronized video from the tripod-mounted camera observing the scene (see Fig. 5). A user manually annotated the moment of abscission in the interface. Wrist force signals and the algorithm's prediction were not shown to the user during manual annotations. We then compared the time stamps from the algorithm's predictions with the user's manual annotations.

3. RESULTS AND DISCUSSION

Figure 6 shows a summary of the actual events compared with the predicted events for 35 unique apple pick attempts. For the heuristic, $Recall = \frac{TP}{TP+FN}$ was 0.90, $Precision = \frac{TP}{TP+FP}$ was 1.00, and the $F1-score = \frac{2*Precision*Recall}{Precision+Recall}$ was 0.95. There is a significant class imbalance with 31 successful picks compared to only 4 failed picks. Note that we only report results for trials where the initial grip phase was successful, which filtered the total number of approximately 100 pick attempts down to 35. The small number of failed picks in the dataset presented here is because, generally, if the initial grip was successful (i.e. a vacuum seal was achieved with the fruit), the pick was usually successful. An example of a successful classification is shown in Fig. 7 where abscission can clearly be seen by the spike in the derivative of the force signal (and the pressure signal indicates that vacuum has been maintained with the fruit). The three false negatives occurred in trials where the force threshold was never reached during the pick phase. While these early results are promising and show the potential value of using force and pressure sensing to detect fruit abscission, in future work we will evaluate our method on a larger dataset of pick attempts.

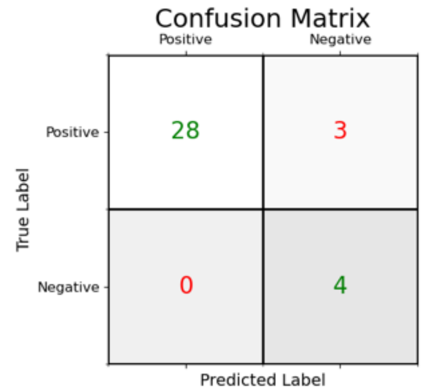

Fig. 6. Confusion matrix that compares the actual event with the heuristic's predicted event for 35 apple picks. A 'positive' is a successful pick and a 'negative' is a failed pick.

For the successful apple picks classified correctly, the average difference between the heuristic's classification time and the user's annotated time was 0.59 seconds. Figure 8 shows the paired time comparisons for the 28 true positives. While there is lag plus variability in the user's reaction time, plus some subjectivity when trying to detect abscission in a video, this result shows that the classification is occurring close to the moment of fruit abscission. Since the heuristic only incorporates straightforward analytical calculations (i.e. vector magnitude, derivative, and filtering), it could easily be integrated for real time operations. Table 1 summarizes the heuristic's overall performance.

Mean (ΔTime) [sec]	0.59±0.42
Precision	1.00
Recall	0.90
F1 Score	0.95

Table 1. Performance results for the heuristic. ΔTime is the difference between the classification time and the time annotated by the user.

Figure 9 shows a histogram of the peak force for each channel over all 35 pick attempts. The dominant force signal for our experimental setup is the z-axis (i.e. the axis normal to the wrist force/torque sensor; see the vector shown in Fig. 2). If the algorithm is evaluated on the 35 pick samples using just the z-channel, leaving out the force signals from the x- and y- channels, the F1-score only drops from 0.95 to 0.93. This result indicates the potential to use single-axis force sensors or load cells, which are substantially less expensive than multi-axis force sensors, without significant loss of performance.

Finally, the threshold value for $d\widetilde{F}(t)$ may need to be tuned when the robot's environment changes. The fruit's mean abscission strength (i.e. the force required to pick the fruit) and limb compliance, which are known to vary by apple variety and tree architecture, will influence the force signal. Abscission strength and the tree's compliance may

[1] https://wiki.python.org/moin/PyQt

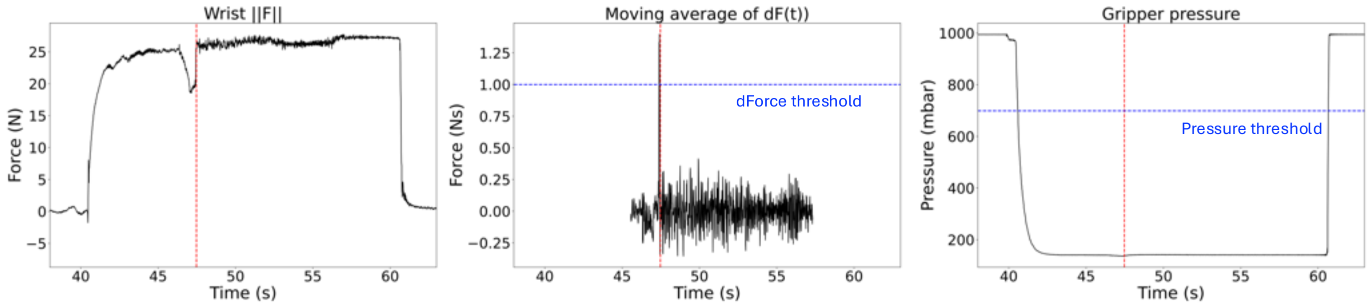

Fig. 7. Results from a successful classification. The apple was separated from the tree at 47.52 seconds. The horizontal blue lines indicate the threshold dForce and pressure values used in the heuristic.

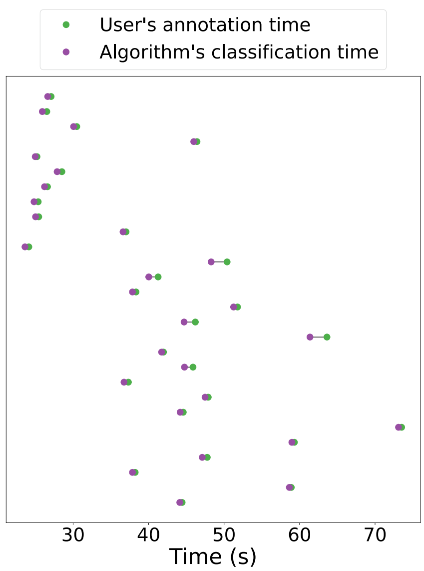

Fig. 8. Comparisons of the heuristic's classification time with the user-annotated abscission time for the 28 true positives, shown as a paired parallel line plot.

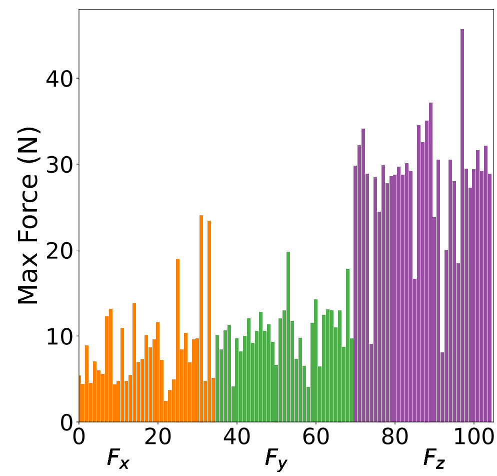

Fig. 9. Peak forces recorded during all 35 pick attempts, separated by force channel (Fx, Fy, Fz). The x-axis represents individual pick attempts (1 through 35, for each force axis). The y-axis shows force magnitude in Newtons (N). Each bar represents the peak value recorded on that channel during a single pick attempt.

even change for the same orchard from year to year. For autonomous, robotic harvesting, the derivative's threshold value could be learned during a calibration procedure at startup.

4. CONCLUSION

In this paper we presented a technique that uses a combination of pressure sensing and force sensing from a wrist-mounted force/torque sensor to detect fruit abscission during robotic apple harvesting. The simple algorithm first looks for spikes in the force signal's derivative, then checks whether vacuum has been maintained. We evaluated our approach on 35 unique apple picks from a real world orchard. The algorithm's F1-score was 0.95 when using all three linear force channels, and inspection of time synchronized videos shows that the classification is happening at, or near, the correct moment. The classification accuracy only drops slightly when using just the z-channel force signal. Our results indicate that in-hand pressure and force sensing may offer useful signals for detecting important events that may be difficult to observe from cameras or vision-based sensors alone. While this study focused on robotic apple harvesting, similar approaches using wrist-mounted force sensing may have potential in other crops involving dynamic picking motions aiming to sever the peduncle at the abscission joint. However, further evaluation under varied conditions and crop types is necessary to confirm broader applicability.

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